CROWDSOURCING FOR SEARCH OF DISASTER VICTIMS: A PRELIMINARY STUDY FOR SEARCH SYSTEM DESIGN

Burnap, Alex (1); Barto, Charlie (1); Johnson-Roberson, Matthew (1); Ren, Max Yi (2); Gonzalez, Richard (1); Papalambros, Panos Y. (1)
1: University of Michigan, United States of America; 2: Arizona State University, United States of America

Abstract

Teams of unmanned aerial vehicles (UAV) have been suggested as sensor platforms for disaster victim search systems used shortly after natural disasters such as an earthquake or tsunami. Previous efforts have used UAVs equipped with video cameras for the disaster information gathering stage, with the information processing stage performed by either a single human searcher or a victim detection computer vision algorithm. We propose extending these efforts by investigating how a large and distributed "crowd" of volunteers may augment the information processing stage by helping search video feeds for disaster victims. An experiment is conducted comparing the victim detection accuracy between a single human searcher, a crowd of searchers, and a victim detection algorithm. Our preliminary results show that while victim search accuracy is sensitive to both UAV altitude and crowd size per video feed, crowdsourcing the search process can be more accurate than a single human or victim detection algorithm alone. These findings are a first step towards optimizing search system design with respect to both information collection and information processing augmented with crowdsourcing.

Keywords: Crowdsourcing and Funding, Disaster Victim Search, Humanitarian Design, Systems engineering (SE)

Contact:
Alex Burnap
University of Michigan
Design Science
United States of America
aburnap@umich.edu

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1 INTRODUCTION

Natural disaster events such as the 2008 Sichuan earthquake in China, 2005 Hurricane Katrina in the United States, 2010 Haiti earthquake, 2009 Tohoku earthquake and tsunami in Japan, and 2004 Sumatran earthquake and tsunami in the Indian Ocean, have caused an unprecedented number of casualties and destruction of both infrastructure and livelihoods. During these disaster events, the majority of initial responders are the immediate survivors themselves, yet oftentimes damage to communication and transportation infrastructure hampers local community efforts for disaster victim search and rescue.

At the same time, it is known that the mortality curve for trapped or stranded victims peaks between 24 and 72 hours after the disaster event (Coburm et al., 1992; Jacoff, 2008; Tadokoro, 2009). During this short window of time, there is a need for rapid disaster victim search so that crews of rescue personnel may perform victim extraction using tools such as air jacks, spreaders, and special purpose vehicles (Tadokoro, 2009). To this end, many efforts have taken a systems engineering approach by decomposing the search process into an information gathering stage and an information processing stage (Cameron et al., 2010; Govindaraj et al., 2013; Mosterman et al., 2014).

Unmanned aerial vehicles (UAV) have been fielded as sensor platforms in victim search systems (Adams and Friedland, 2011; Cooper and Goodrich, 2008; Doherty and Rudol, 2007; Murphy, 2014). The idea to conduct the information gathering stage using a team of UAVs, each equipped with camera systems operating in both the visible and infrared spectrums (Doherty and Rudol, 2007; Flynn and Cameron, 2013; Rasmussen et al., 2009), or cell phone signal detectors (Wang et al., 2013). The subsequent information processing stage is then conducted by either a single human searcher co-located with the UAV (Murphy, 2014) or from an automated computer vision algorithm on-board the UAV (Quaritsch et al., 2010; Symington et al., 2010; Waharte and Trigoni, 2010). When disaster victims are identified during this search process, their locations are marked with GPS waypoints for subsequent rescue by disaster response teams.

While these search system designs have proved effective for their use cases, their effectiveness is limited to relatively small geographic regions when compared to the vast scale of affected regions during a natural disaster event. To search much larger areas, we are motivated by recent examples of online crowdsourcing used in response to natural disasters—including thousands of volunteers who mapped road blockages and building collapses using satellite imagery during the 2010 Haiti earthquake, 2013 Typhoon Haiyan, and 2014 Malaysian flight MH370 (Goodchild and Glennon, 2010; Starbird, 2011; Zook et al., 2010).

In this work, we investigate how crowdsourcing may enable scalable search system designs by relaying video feeds over the internet to a *large and untrained* crowd of search volunteers. An experiment is conducted assessing the crowd's detection accuracy relative to current victim detection methods; namely, a single human searcher or a computer vision algorithm. Two search system design variables are tested—video feed altitude and crowd size per video feed—corresponding respectively to the information gathering stage and the information processing stage.

Our results show that at medium (50 m) and high (100 m) altitudes, crowdsourcing matches and even outperforms both a single human searcher and the computer vision algorithm. In particular, we find that the crowd's majority vote is able to correct for false positives and false negatives from single human searchers; behaviour that is shown to plateau at crowd sizes of 5 people per video feed. At low altitudes (10 m), the computer vision algorithm significantly outperforms the crowd, suggesting crowdsourcing may be less useful for "fine-grained" searching.

The contribution of this work is a quantitative justification that *large and untrained* crowds may enable scalable search system designs, thus enabling search coverage of vast geographic regions of affected area. This contribution subsequently underpins existing and on-going efforts towards detecting victims of disaster events during the crucial 24-72 hour post-event time window, and supports future work towards crowdsourced information processing for more general search system designs.

The rest of this paper is organized as follow: Section 2 introduces relevant academic work and disaster victim search efforts using UAVs. Section 3 introduces the experimental procedure, description of the video feeds and crowd participants, and results obtained. Section 4 discusses the results. Section 5 offers implications and future directions. Section 6 concludes with a summary.

2 LITERATURE REVIEW

Unmanned Aerial Vehicles for Disaster Response Search Systems

Various robotic search systems have been actively fielded in over 34 different disasters to date, extending as far back as the 1995 Alfred P. Murrah Federal Building bombing in Oklahoma City (Murphy, 2014). While these robotic systems have primarily been ground-based, the earliest use of UAVs occurred during the 2005 Hurricane Katrina (Adams and Friedland, 2011; Murphy, 2014). These actual deployments have largely consisted of fewer than five robots deployed after the critical 24-72 hour time window of victim mortality.

There has been a recent surge in large-scale efforts to use UAVs for disaster victim search systems, such as ICARUS in the European Union (Govindaraj et al., 2013), SERS in the U.S. (Mosterman et al., 2014), and SUAAVE in the U.K. (Cameron et al., 2010). This state-level recognition for increased research and development of humanitarian UAVs is further supported by the recently released United Nations policy brief on the use of UAVs for humanitarian missions (Gilman, 2014).

Human Detection using UAVs

Research studies using actual UAV prototypes for human detection are important to this feasibility study as they give reference points for identifying design variables such as UAV type and flying characteristics, UAV payload considerations, and video feed transmission constraints. Research in wilderness search and rescue (Goodrich et al., 2009; Tomic et al., 2012) suggests that while small fixed-wing UAVs may maintain longer flight durations and can cover more area, they are more suitable for capturing still images than video feeds due to altitude, speed, and flight characteristics (Gaszczak et al., 2011). In contrast, small rotary-based UAVs such as quadcopters can hover in place when needed and can operate at altitudes from just a few meters to well over 100 meters (Adams and Friedland, 2011; Murphy, 2014; Ollero and Merino, 2004; Symington et al., 2010).

Much of the reviewed literature using rotary-based UAVs focuses on automated detection of victims using a computer vision algorithm, either on-board the UAV or relayed back to a central processing server. These computer vision algorithms include Haar feature cascades (De Cubber and Marton, 2009; Rudol and Doherty, 2008), HOG feature classifiers (Andriluka et al., 2010), and ensembles of both (Soni and Sowmya, 2012). These algorithms have additionally included online training for increased accuracy as more disaster scenes are captured (Soni and Sowmya, 2012; Waharte et al., 2010). Multi-modal learning approaches for sensor fusion have also been used to combine signals from multiple sources such as optical and infrared video cameras (Flynn and Cameron, 2013; Rudol and Doherty, 2008).

In contrast, literature using humans for search via a video feed or images primarily comes from actual disaster deployments. During these deployments, three-person operator teams including a pilot, searcher, and flight director have empirically been found to be successful for searches (Murphy, 2014). Practical considerations affecting a human searcher's ability to detect victims include occlusion and avoidance from obstacles (Murphy, 2014), as well as jitter correction from video (Goodrich et al., 2009).

Crowdsourcing

While UAV efforts using human searchers for victim detection involve searchers co-located with the UAV operation team, this study is motivated by recent examples of using crowdsourcing for disaster response in which crowd members were distributed throughout the world via the internet. Perhaps the earliest examples in this vein are the uses of social media outlets as passive forms of crowdsourcing for gathering disaster information. In particular, blogs and user-uploaded video provided one of the quickest news sources for disasters such as the 2004 Indian Ocean Earthquake and Tsunami and 2005 Hurricane Katrina (Goodchild and Glennon, 2010; Laituri and Kodrich, 2008).

Recently, more directed forms of crowdsourcing for disaster response have been fielded in which crowd members tag satellite imagery of destroyed buildings and road accessibility for use by on-the-ground disaster response teams (Zook et al., 2010). Efforts along this direction are supported by a multitude of internet-based communities including the Humanitarian OpenStreetMap mapping infrastructure (Starbird, 2011; Zook et al., 2010), and the Digital Humanitarian Network (Meier, 2014).

3 EXPERIMENT AND RESULTS

The goal of this experiment is to assess whether or not crowdsourcing may improve a disaster victim search system by comparing the victim detection accuracies of a single human, a crowd of humans, and a computer vision algorithm. Moreover, as disaster victim search systems may be divided into a disaster information gathering stage and a disaster information processing stage, this experiment tests the effect of two search system design variables, video feed altitude and crowd size per video feed.

Participants

Participants were gathered through the crowdsourcing platform Amazon Mechanical Turk. A total of 181 participants were sourced from locations distributed all over the world, including 13 countries, with a majority of participants from the United States, India, and China. These location demographics were obtained by geo-locating the IP addresses of participants. The self-reported age distribution of the participants had average age of 32.9 years old. The self-reported gender identification of the participants resulted in 45.1% Female and 55.9% Male. Note that while all participants in this study are purportedly anonymous via Amazon Mechanical Turk, we took additional anonymity measures via randomized identity hashing and data encryption.

Video Feeds

The video feeds used in this study were not of real disaster scenes due to lack of publicly accessible footage or ability to generate footage. Instead, video feeds analogous to those captured from a UAV flying over a disaster event were used. These video feeds included scenes with both victims present and victims not present, as well as video feeds with shakiness representing video jitter induced by UAV flight interactions with wind (Alexis et al., 2010; Bernard et al., 2011).

Figure 1. Example frames from the three video feeds corresponding to three altitudes: (a) low ~ 10m, (b) medium ~ 50 m, and (c) high ~ 100m. Each example frame shown has a human present (highlighted in red) to illustrate relative size of human versus video frame.

Three video feeds were used in this study as shown in Figure 1, corresponding to three altitudes: low altitude (10m), medium altitude (50m), and high altitude (100m). The low altitude video feed was taken using a handheld video camera from a building on the University of Michigan engineering campus using waivered volunteers, similar to Flynn and Cameron (2013). The medium and high altitude video feeds were taken from the VIRAT Aerial Video dataset (Oh et al., 2011), in which the video feed was captured using a UAV. Each of the three video feeds was 120 seconds long, made up of twelve 10 second clips cropped using lossless video editing software. All three videos have a resolution of 720 x 480 and a frame rate of 29.97 frames/second. Lastly, each of the three video feeds had a corresponding ground truth made up of twelve 0's or 1's representing whether or not a human was present in each of the 10 second clips.
To obtain ground truth labels for the three video feeds, expert labelling was conducted via frame-by-frame analysis. This analysis additionally used information about the scene that was not included in the three video feeds, including the locations and activities of "victims" seen at low altitudes directly before and after a high altitude video capture. The video feeds were stitched together to ensure a half-half distribution of ground truth 0's and 1's, ensuring that 50% was random chance detection accuracy.

Single Human Searcher and Crowd of Human Searchers

We define a single human searcher as simply one participant who viewed a video and attempted to detect disaster victims. A crowd of human searchers is defined as a set of human searchers that viewed the same video feed and attempted to detect disaster victims. To obtain *C* crowds of human searchers, we uniformly sample *p* participants from the set of all single human searchers. This random sampling is done without replacement within a single crowd indexed by *c*, but with replacement across the overall *C* crowds. The size of crowd per video feed *p* is treated as a search system design variable, while the number of crowds *C* is used only to obtain average and standard deviation statistics during data analysis.

Computer Vision Algorithm

The computer vision algorithm used in this study for detected victims was a HOG cascade using a support vector machine classifier. Though notable previous research has used Haar features (De Cubber and Marton, 2009; Rudol and Doherty, 2008), HOG features were chosen as they are a benchmark standard within the computer vision community, as well as having performed better than Haar features on our pilot tests.

Our open source classifier implementation included a benchmark classifier from the OpenCV package, which was accelerated using the graphical processing unit (GPU). While traditional HOG-feature classifiers operate on single frames, our implementation was extended by only reporting presence of a victim if a number of previous frames included a bounding box within a threshold distance. The number of previous frames as well as threshold distance were treated as tuneable parameters, in addition to traditional parameters for the HOG classifier including the window size and hit threshold (Zhu et al., 2006).

Procedure

A web application with a database backend was developed as an interactive survey to display video feeds and gather victim identification from the crowd ("CrowdSAR," 2014). Participants were first directed to an introduction page, where participants were asked to click on their screen to identify humans in the video feed. Next, participants were directed to the video page and given the instructions again in pictorial format. Upon confirming understanding of the instructions, each participant was randomly given full screen video of one out of the three possible video feeds corresponding to the three tested altitudes. During this 120-second process, each time participants clicked their screen for victim identification and their mouse click was recorded and saved to the database. Real-time participant feedback during this process included time remaining as well as current victim identification accuracy.

Data Analysis

To quantify the victim detection accuracy of a single human searcher, a crowd of searchers, and the computer vision algorithm, a binary classification error metric is chosen. Each video feed includes twelve 10-second segments, resulting in victim detection accuracy per video feed for a single searcher (human or computer vision algorithm) given by Equation (1),

$$\frac{1}{12}\sum_{v=1}^{12}\mathbf{I}\ \text{, where } \mathbf{I}=\begin{cases} 1\ if\ x_v^{(i)} = g_{a,v} \\ 0\ else \end{cases}, \tag{1}$$

for video segment *v*, searcher *i*, altitude *a*, ground truth $g_{a,v}$ denoting whether or not a human exists in video segment *v*, and with $x_v^{(i)}$ denoting whether searcher *i* clicked on video segment *v*.

Subsequently, the average victim detection for single human searchers is determined by averaging all participants for each altitude. Note that the computer vision algorithm is deterministic, and accordingly does not have average and standard deviation statistics.

The crowd's victim detection accuracy is determined similarly to Equation (1), with the change in whether the crowd clicks on a particular segment $x_v^{(c)}$.

$$\frac{1}{12}\sum_{v=1}^{12} \mathbf{I} \text{ , where } \mathbf{I}=\begin{cases} 1 \text{ } if \text{ } x_v^{(c)} = g_{a,v} \\ 0 \text{ } else \end{cases} \tag{2}$$

In particular, we assume a majority vote rule for the crowd consensus (Sheng et al., 2008; Tang and Lease, 2011), where we set $x_v^{(c)} = 1$ if a majority of crowd c clicks on video segment v, and $x_v^{(c)} = 0$ otherwise. In the case of ties from an even number of crowd members, we set $x_v^{(c)} = 1$. To calculate average and standard deviation for the crowd, we sampled C=100 crowds of size p, in which p was used as a search system design variable.

Results

The victim detection accuracy for a single human searcher, a crowd of human searchers, and the computer vision algorithm is plotted in Figure 2. A crowd size of five participants per video feed was chosen for determining the crowd's detection accuracy in Figure 2.

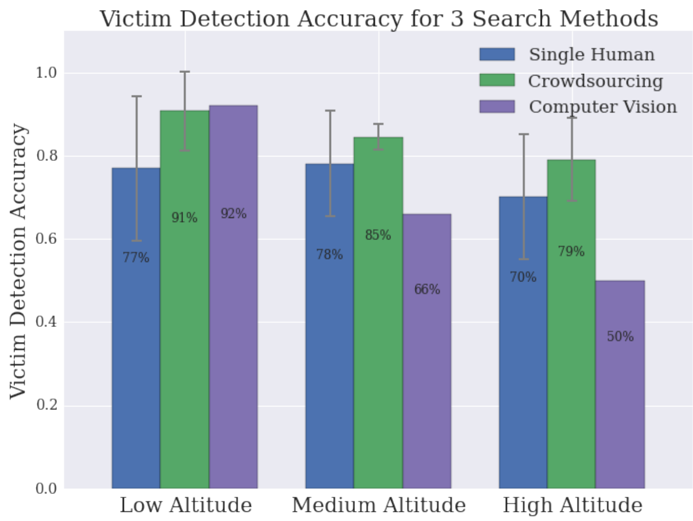

Figure 2. Victim detection accuracy for a single human searcher, a crowdsourced search, and the computer vision algorithm at low, medium, and high altitudes. Error bars indicate one standard deviation.

The relationship between victim detection accuracy and crowd size per video feed at each altitude is plotted in Figure 3.

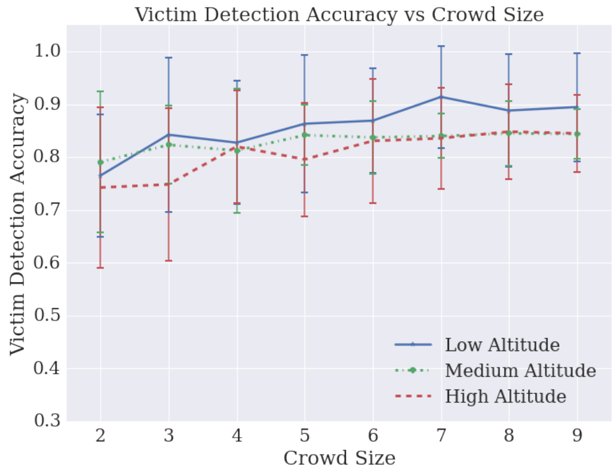

Figure 3. Empirical relationship between the crowd's victim detection accuracy and crowd size per video feed. Error bars indicate one standard deviation.

4 DISCUSSION

Addressing the purpose of this study, crowdsourcing is able to match or outperform both a single human searcher and the computer vision algorithm at medium (50 m) and high altitudes (100 m), altitudes in which UAVs would need to operate at to cover vast regions of disaster-affected area. This result indicates that crowdsourcing may indeed enable scalable information processing for search systems designed to search over vast regions of disaster-affected area, particularly as these altitudes are necessary for reasonable search coverage.

Moreover, the average crowd's detection accuracy *exceeded* that of the average single human accuracy at all altitudes. This finding highlights the tenet that the crowd's majority vote is often more robust than its single members (Hong and Page, 2004), particularly for tasks that are 'simple' for most humans such as image and video recognition (Burnap et al., 2014). Still, this finding must be held conservatively in the context of this study, as single human searchers considered here are defined as the average crowd participant; in contrast, previous fieldings with UAVs have used trained experts for the video feed information processing task.

At the lowest altitude (10 m), the computer vision algorithm described in Section 3 was able to detect victims better than either a single human searcher or a crowd of human searchers. At medium altitudes, a difference of 7% emerges between the crowd and single humans, while the computer vision algorithm precipitously drops 66%, nearly random guessing (50%). At this altitude, humans (when present) occupy roughly only 0.1% of the video image area as shown in Figure 1, explaining the relatively poor performance of the computer vision algorithm. At high altitude, victim detection ability drops for all search methods, but drops least for crowdsourcing.

With these results and given the current state of computer vision algorithms, human searchers will likely continue to outperform computer vision algorithms at high altitudes within the near future. Current computer vision algorithms for human detection are typically trained on benchmark datasets that are very different from those of a disaster scene. As a result, performance of pre-trained algorithms is likely decreased on these "out of sample" disaster scenes. A possible remedy is re-training with different, more appropriate datasets. Furthermore, comparisons between single humans and crowds for all altitudes show that crowds are even able to outperform single humans. For each video segment v, the crowd's majority vote was able to correct for false positives and false negatives from single human observations.

Limitations

While these results suggest that crowdsourcing has the potential for improving the disaster information processing stage for a disaster victim search system, we must note that a number of limitations exist to these preliminary findings:

First, as described above, we have assumed that single human searchers are the "average" participant in the crowd. More realistically, these single human searchers would be trained experts in searching for disaster victims. While such training would likely involve standardized tests for situational awareness, it is not unreasonable to imagine methods of finding and training such "experts" in the crowd.

Second, we assumed that the video data set used for simulating disaster video feeds has direct applicability to what may be found with a real disaster. As stated before, most likely computer vision algorithms would do even worse given the non-generalizability of their training sets, yet it is not clear whether or not a human would exhibit similar search accuracies as found in this study. Moreover, even the video data sets used in this study were not of the same scenes for the low, medium, and high altitudes; instead, we relied on drone video from benchmark datasets (medium and high altitude) as well a self-generated video data (low altitude).

Third, we assumed perfect latency and syncing of videos for video feeds. In reality, the communications system necessary to sustain a sparsely distributed ad-hoc network to deliver real-time or near-real-time video streams is a challenge, as studied recently (Burdakov et al., 2010; Qiantori et al., 2012; Tuna et al., 2014).

Implications for Future Work

These preliminary results motivate further efforts in the design of disaster victim search systems. Regarding the use of crowdsourcing the information processing stage, many pertinent questions remain that require qualitative analysis methods. In particular, human factors must be considered including the willingness of participants to search for victims in videos feeds containing graphic imagery of gore and death, and participant perceptions on how their inputs contribute to the overall disaster response effort. It is important to understand the underlying motivations of participants to volunteer for a crowdsourced disaster victim search system, including preferences between fiscal and physical contribution (Stoianova, 2012), as previous findings have shown relative discrepancies in propensity to volunteer between different types of disasters. Along these lines, there are likely to be significant legal and political obstacles both at the victim and state level to relaying sensitive video feed of disaster zones.

The user interface for the web application that relays disaster video can be improved with video playback controls such as rewind, slowdown, and zoom. There is likely an optimal amount of user interface to balance control with situational awareness (Billings and Durlach, 2008). Processing techniques to correct for video jitter must also be considered as they are a large source of user error and frustration (Goodrich et al., 2009). Example methods to correct for this jitter include better gimbal mounts and video processing techniques such as video feed mosaicking (Morse et al., 2008).

To improve the accuracy of the crowd, methods of aggregating the crowd's input that give expert searchers more weight may be advantageous. Such crowd consensus models have been studied extensively within the crowdsourcing community (Bachrach et al., 2012; Caragiannis et al., 2013; Sheshadri and Lease, 2013), including methods of implicitly and explicitly determining the experts. It is especially important to understand under which conditions simple crowd consensus aggregation methods such as majority vote break down (Burnap et al., 2014). Along this direction, methods of combining both human searchers and computer vision algorithms may be fruitful, as such methods may play to the relative strengths of each in a combined search system. Such a combined search system may use humans for improving computer vision algorithm during training, as well as used sequentially with the computer finding "regions of interest" followed by human verification.

Many other search system design variables can contribute to victim detection accuracy besides optical video feed. Multiple sensors such as infrared video (Doherty and Rudol, 2007; Flynn and Cameron, 2013; Rasmussen et al., 2009), Wi-Fi and cell phone signal detectors (Wang et al., 2013), and audio signals may be used. Multiple sensor selection currently involves sensor fusion rules dependent on UAV altitude and flight characteristics. These rules can be turned into more rigorous decision-making tools by taking advantage of improvements in multi-modal and online learning (Soni and Sowmya, 2012; Waharte et al., 2010).

Finally, system-level optimizations that incorporate simulation models of disasters, victim locations, and victim conditions (Coburm et al., 1992; Imamura et al., 2012; Katada et al., 2006); empirical data from previous disasters (Boyd, 2010; Suppasri et al., 2012); and various search system design variables such as number of UAVs and bandwidth capabilities must be performed to help inform macro-level variables for the design of a disaster victim search system. Such system-level optimization may extend previous findings for maximizing coverage maps under UAV constraints

(Burgard et al., 2002; Sujit and Ghose, 2004). Decision-support systems that maximize coverage using hybrid human and computer scene analysis to iteratively identify “regions of interest” are also potentially valuable here, as they have shown results in crowdsourced video summarization (Lee et al., 2012; Vondrick et al., 2013). Such coverage map simulations and decision-support systems may extend this study to optimize UAV altitude during different portions of the information processing stage.

5 CONCLUSION

Unmanned aerial vehicles (UAV) have been recently used in search system designs to locate disaster victims during the critical 24-72 hours immediately following a natural disaster event. These search systems have receiving increased attention due to an unprecedented frequency of natural disaster events in the last decade, as well as advances in UAV and sensor technology. While these search system designs have proven effective, they are limited geographically due to having information processing performed by a single human searcher or a computer vision algorithm.

To enable search of large regions of disaster-affected area, we have proposed crowdsourcing the information processing stage by sending video feeds from teams of UAVs to a crowd of search volunteers. To this end, an experiment was conducted testing whether a large and untrained crowd was able to match victim detection accuracy of a single human searcher or a computer vision algorithm, using videos feeds captured at low (10 m), medium (50 m), and high (100 m) altitudes.

Results show that crowdsourcing was able to not just match, but even outperform victim detection accuracy of a single human searcher and the computer vision algorithm. Importantly, these findings were displayed at medium and high altitudes—altitudes necessary for searching large regions of disaster-affected area. The results of this study suggests that crowdsourcing may indeed enable scalable information processing for search system designs.

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